A Prognostics Approach for Gearbox based on Spectrogram and Deep Learning

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ABSTRACT

This paper presents a method and solution for Asia Pacific Conference of the Prognostics and Health Management 2017 Data Challenge. Considering the complex of gearbox signal, a novel approach utilizing spectrogram and deep learning is proposed. Spectrogram can transform the raw signal into time-frequency space that is an effective method to process vibration signal of gearbox. Deep learning is a useful method that has the ability of automatically feature learning. The spectrogram is obtained by using short-time Fourier transform (STFT). Then, the way of the stacked auto-encoders (SAE), is trained to auto-extract feature and realize the prediction. For diagnosis, the cepstrum algorithm is performed to simplify the spectrum and find the most severely-degraded component. This solution earned the 3rd highest score of the results from all teams in the competition, which demonstrate the effective of proposed method.

1. INTRODUCTION

The PHMAP data challenge 2017 is focused on tracking the healthy state of components and predicting the date of upcoming gearbox replacement. Sensors data from the pulverizes were collected.

Time-frequency analysis is an efficient method to deal with the vibration signal from rotating machinery. Inspired by the field of speech recognition, the spectrogram is introduced in this paper. After short-time Fourier transform (STFT), which can transform the raw signal into time-frequency space, the spectrogram is generated. A spectrogram is a visual display of the distribution of energy across frequencies and over time and intensity represents power at each time–frequency point.

For prognostics, a high prediction accuracy requires appropriate feature extraction. Affected by the characteristics of vibration signals, each tradition feature method has own shortcomings. Especially the signal of gearbox is complex because of the modulation and impulsive. Considering the affection of noise, it is a huge challenge and traditional method can't complete the task satisfactorily. Unlike the traditional method, deep learning can extract feature automatically. It provide more abstract characteristics of the original data utilizing its excellent feature learning ability.

Therefore, a method combined of spectrogram and deep learning is proposed to solve the prediction problem in this paper and a cepstrum-based method is introduced to solve the diagnosis problem.

This paper is organized as follows: Section 2 present the methodology including spectrogram, deep learning and cepstrum; Section 3 is a case study for the data of PHMAP data challenge 2017; In Section 4, conclusions are drawn and future work is discussed.

Fault in gear brings about impulsive modulation, including amplitude and frequency modulation, of the gearmesh signal. Large numbers of sidebands appear at the meshing frequency of fault gear. Therefore, Spectrum is not suitable for gearbox diagnosis. A proved ideal method for complicated multiband frequency analysis is the cepstrum analysis, which has widely application for detection harmonics with uniform spacing of modulation sidebands commonly found in gearbox. Cepstrum is an analysis of logarithm spectrum of a signal and gather the information of large number of sidebands into relatively small number of harmonics. In other words, the cepstrum analysis simplifies the original spectrum.

2. METHODOLOGY

The main procedure of predicting the date of upcoming gearbox replacement and fault diagnosis is illustrated in the Fig. 1. There are three main steps：

(1) The vibration signal is analyzed by using short-time Fourier transform (STFT) and then spectrogram is obtained.

(2) Cepstrum analysis is employed to realize the fault identification.

(3)The data of replacement is predicted based on deep learning.

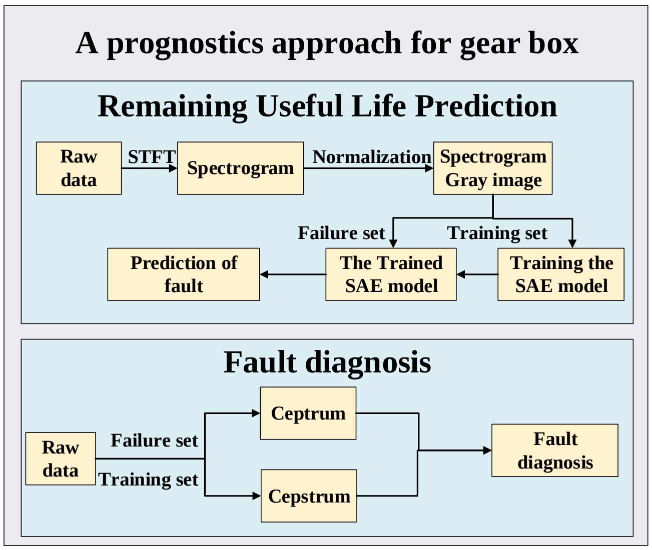

Fig 1. Schematic diagram of prognostics and diagnosis for gearbox

2.1. The analysis of vibration signal using spectrogram method

As the typical rotation machinery, the frequency domain feature of vibration signal can characterize the performance of gearbox. The vibration signal can transform from the time domain to frequency domain by utilizing Fast Fourier Transform (FFT).

STFT is optimization of FFT to deal with non-stationary signal and it is employed to generate the spectrogram [1]. After multiplying the raw data by a window, the signal is truncated into small data frames. FFT is applied in each short data frame. The spectral amplitude matrix is constructed according to the results of signal process using STFT. Defined the power spectrum density (PSD) as a matrix whose element value is the square of element value of spectral amplitude matrix.

The spectrogram algorithm is to produces a spectrogram based on STFT and PSD. The spectrogram is two-dimensional image representing the signal taking the time as abscissa axis and frequency as the ordinate axis. And Pseudo Color Map (PCM) demonstrate the PSD in the image.

For each spectrogram, Min-Max Normalization normalizes the elements value of column to an integer form 0 to 255. Then, the gray images are generated.

2.2. The prediction of fault based on deep learning

Deep Learning is a branch of machine learning and the fundamental of deep Learning realize the exacted features by themselves. Stacked Auto-Encoder (SAE) is one of the mainstream deep learning model [2]. In this paper, SAE is chosen to realize the feature learning and prediction. SAE model is trained by the spectrogram data and normalized date as the input and output. Then, feeding the testing spectrogram data to the trained model, the predicted date data can be obtained.

2.2.1. Auto-Encoder

The Auto-Encoder (AE) is a Feedforward Neural Network (FFNN) with three layers, as depicted in Fig. 4. A trained auto-encoder can encode the raw data into some low-dimensional feature and reconstructed by a decoding process, therefor the AE is used as an unsupervised feature learning algorithm [3].

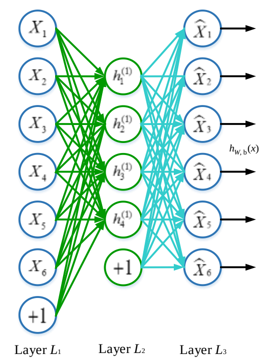

Fig 2 The structure of Auto-Encoder

Suppose the input sample as x , the mapping of encode and decoder is as follows:

$$y = sigmoid(Wx + b)$$
$$z = sigmoid(W^T x + b^T)$$

that W is the weight of networks and b is the offset vector.
The auto-encoder measure the differences between the reconstructed input and the raw data via the cost function and minimize the error by optimizing the model.
In addition, the auto-encoder was forced by the sparsity constraint on the hidden modes. Sparsity means the neuron is “inactive” most of the time.

2.2.2. Stacked Auto-Encoder

SAE model is a deep learning network constructed by multilayer auto-encoder. The outputs of each layer will be to wired the inputs for the next layer in the sequence. Each layer generate a more abstract characterization, therefore, the SAE model will output a high level representation of raw data.

2.2.3. Fine tuning

To greatly improve the performance of SEA model, the fine tuning based on BackPropagation (BP) is necessary. According to the date label information, in each iteration, all of the weights in SAE are optimized. Therefore, the predictive accuracy of SAE model will improve.

2.3. A cepstrum-based fault diagnosis for gearbox

Cepstrum is an effective way to identify faulty for rotating machinery [4]. Common cepstrum analysis include four method, real cepstrum, complex cepstrum, power cepstrum and phase cepstrum.

The real cepstrum is performed in this paper. The essence of real cepstrum is taking the inverse Fourier transform (IFT) of the logarithm of the spectrum of a signal [5]. The process of the real cepstrum analysis can be can be summarized as Fig 3.

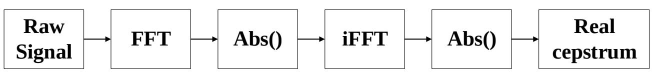

Fig 4 The process of cepstrum

The cepstrum simplified the interpretation of correlation between sideband families and fault in gears. Comparing the amplitude of specified frequency, the fault can be easily identified through the cepstrum.

3. CASE STUDY

3.1. prediction of the replacement date

For pulverizer A, B and E to be predicted, the vibration signal (including acceleration data, displacement data and velocity data) were chosen as the raw data. For each group signal transform the displacement data and velocity data into acceleration data with derivation and then the three types of data were connected in series as new data.

Each signal was processed to identify its sampling frequency. For different sampling frequency (7680Hz and 2048Hz), the parameters of STFT are different.

Spectrogram was employed for all of the testing and failure data and then normalization was performed to map the element to an integer from 0 to 255.

Figure. 4 and Figure. 5 shows a sample result of the spectrogram and gray image respectively.

Calculate the day that each pulverizer has been running (defined the first date given in the data set as 0) and normalization the number of days as the labels that are the outputs of SAE model. Selected the SAE model's inputs from the gray image. Then the SAE models of different pulverizers, different sampling frequency and different sampling cases are trained separately.

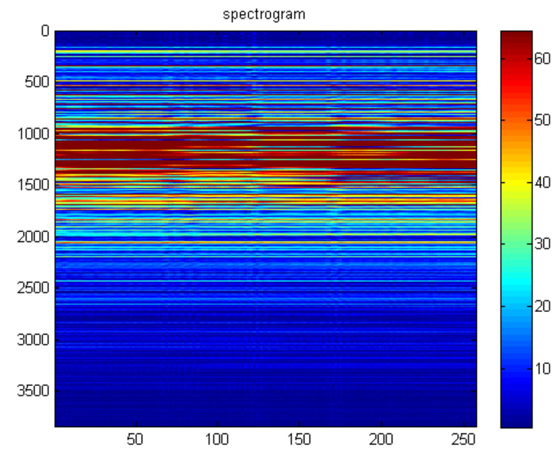

Figure. 4 Spectrogram

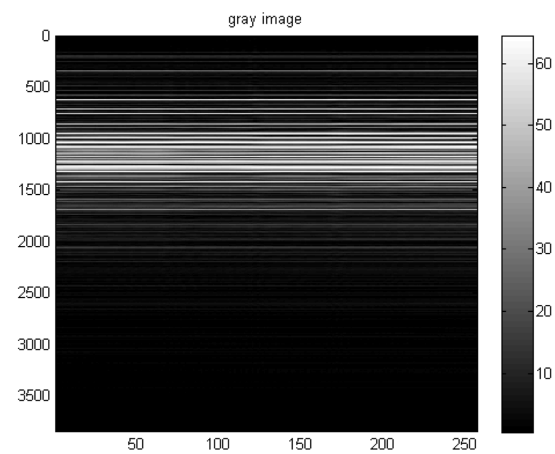

Figure. 5 Gray image

For pulverizer A and B, the failure data used corresponding SAE model to predict the life of pulverizer. Calculate the mean value as the final predicted day.

For pulverizer E , due to the lack of failure data, SAE models of pulverizer A and B are employed to predict the life of pulverizer E, considering the similarity of pulverizer and the degradation of performance are similar. For each group signal of pulverizer E, the SAE model is used to predict the day. Calculate the mean error between the predicted day and actual day. The final predicted day is determined with the final predicted day of A or B and the error.

3.2. finding the most severely-degraded component

According to the specification of pulverizer and gearbox, calculate the meshing frequency of each component. Each signal was processed by cepstrum analysis. Figure.6 shows a sample result of cepstrum.

Compared the amplitude of meshing frequency and its harmonic. Found the amplitude with significant increase and the frequency this point corresponds is fault feature frequency.

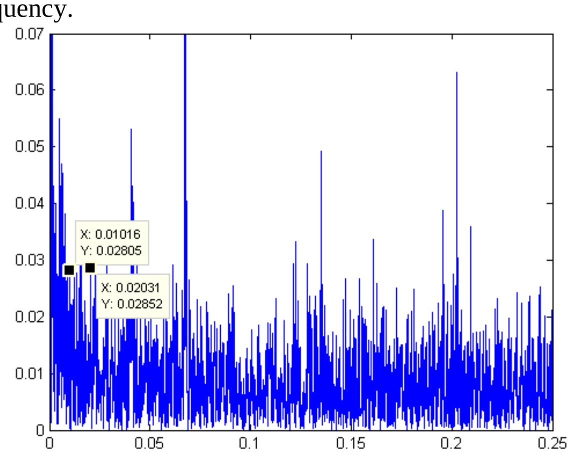

Figure.6 Cepstrum

The most severely-degraded components of for pulverizer A, B and E are all planetary gear.

4. CONCLUSION

This paper introduced a prognostics approach based on spectrogram and deep learning and a cepstrum-based diagnosis method.In the proposed method, the original data are transformed into a spectrogram with frequency information by STFT. Then, the SAE model, which is a deep learning method, is trained to predict the replacement data. Last, diagnosis is realized by the cepstrum algorithm and the most severely-degraded component is found.

This method is a solution for PHMAP 2017 data challenge and it was verified by the data of chanllege. The solution earns the 3rd highest score of the results from all teams. This reveal the method is effective and the satisfactory prediction accuracy is acquired.

The proposed method is easier to have widely application not only for gearbox but also for other rotating machineries because of its data-driven attributes. In addition, on the basis of frequency domain information generated by spectrogram, the deep learning extracts the fault features of gearbox automatically to Overcome the drawbacks of traditional feature extraction method.

The spectrogram and deep learning method consume a vast and amount of memory and time. Therefore the method has a higher requirement for computing equipment and might not be sufficiently satisfactory in “real time”. In our future work, the algorithm will improve to be faster and efficiency. At the same time, mining the meaning of feature auto-extracted by deep learning to improve its accuracy and adaptability.

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REFERENCES

[1] Lampert, Thomas A., and S. E. M. O'Keefe. "On the detection of tracks in spectrogram images." Pattern Recognition 46.5(2013):1396-1408

[2] Ma, J., (2015). Study on Fault Diagnosis of Electromechanical Products Based on Cognitive Computing: A Deep Learning and Transfer Learning method. Doctoral dissertation. Beihang Uniersicy, Beijing, China.

[3] Liu, H., Li, L., & Ma, J. (2016). Rolling bearing fault diagnosis based on stft-deep learning and sound signals. , 2016(2), 12.

[4] Randall, R. B. (2016). A history of cepstrum analysis and its application to mechanical problems. Mechanical Systems & Signal Processing.

[5] Liang, B., Iwnicki, S. D., & Zhao, Y. (2013). Application of power spectrum, cepstrum, higher order spectrum and neural network analyses for induction motor fault diagnosis. Mechanical Systems & Signal Processing, 39(1–2), 342-360.